CLASSIFICATION OF DIABETIC RETINOPATHY STAGES USING DEEP LEARNING ARCHITECTURES

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1. INTRODUCTION

Diabetic Retinopathy (DR) is a common and serious complication of Diabetes Mellitus, caused by prolonged high blood sugar levels. It results in damage to the retinal blood vessels, which supply oxygen and nutrients to the retina. If left untreated, DR can progress and eventually lead to permanent vision loss [1]. One of the biggest concerns with DR is that it often shows no noticeable symptoms in the early stages, making early diagnosis difficult. DR is typically classified into two main types: Non-Proliferative Diabetic Retinopathy (NPDR) – the early stage, which progresses from mild (with small microaneurysms) to moderate and severe (with hemorrhages and blocked blood vessels) [2]. Proliferative Diabetic Retinopathy (PDR) – the advanced stage, marked by the growth of abnormal blood vessels (neovascularization) that can bleed into the eye and lead to severe vision impairment or blindness [3].To address the growing burden of DR, automated detection using deep learning (DL) techniques has become a major focus of research. Convolutional Neural Networks (CNNs) have shown better performance in medical image analysis, as they can automatically extract complex features from retinal images and classify them into DR stages more effectively than traditional methods.

However, existing deep learning approaches still face some challenges despite their success:

- Incomplete detection of all DR stages, especially subtle changes in early NPDR.
- They are highly complex and difficult to use in real-world situations with limited resources [4].

To overcome these challenges, recent research has focused on improving model accuracy and generalization using advanced DL techniques like transfer learning and lightweight architectures. These strategies help reduce overfitting, handle smaller datasets, and make models more scalable and efficient for deployment in clinical practice [5]. Hence, the DR research is moving toward building robust, efficient, and accurate AI-based diagnostic tools that can support early detection, timely intervention, and large-scale screening, especially important in under-resourced regions.

2. LITERATURE SURVEY

The literature survey highlights key research areas in automated DR detection. It focuses on identifying Microaneurysms (MAs), Hemorrhages (HEMs), and Exudates (EXs), which are essential for diagnosing DR. It also reviews approaches for classifying the four DR stages as normal, mild, moderate and severe using advanced machine learning and deep learning techniques. Studies leverage large annotated datasets and pre-trained models to enhance accuracy while addressing issues like overfitting, computational cost, and validation reliability. These advancements support the creation of robust and scalable DR screening systems that enable early diagnosis and timely treatment, especially in regions with limited access to ophthalmologists.
A two-step MA detection framework using Deep CNN (DCNN) is proposed, where the first DCNN detects candidate MAs and the second reduces false positives. This hybrid method enhances feature extraction using Gabor filters, Hessian-based shape indices, and double-ring filters. The approach, tested on the DIARETDB1 database, achieves high sensitivity and precision, highlighting the effectiveness of stepwise DCNN integration in accurately detecting Mas [6]. A novel method [7] for bleeding detection in retinal fundus images uses convolutional sparse image decomposition to fuse extracted features. Using 1,509 images from HRF, DRIVE, STARE, MESSIDOR, DIARETDB0, and DIARETDB1, the approach achieves an average accuracy of 92.71%, outperforming previous methods. A CNN-based method for exudate detection starts with data preprocessing to standardize exudate patches, followed by ROI localization for feature identification [8]. Transfer learning with pretrained models like Inception-v3, ResNet-50, and VGG-19 extracts features. Experimental results show that this pretrained CNN-based system outperforms current methods, excelling in exudate detection in retinal images.

The study in [9] uses two models: CNN512, which classifies entire images into DR stages, and an adapted YOLOv3 model for lesion detection and localization. CNN512 achieves classification accuracies of 88.6% and 84.1% on the DDR and APTOS Kaggle 2019 datasets, respectively, outperforming existing methods. YOLOv3 achieves a mean Average Precision (mAP) of 0.216 for lesion localization on the DDR dataset. The fusion of CNN512 and YOLOv3 boosts performance, achieving an overall accuracy of 89%, with 89% sensitivity and 97.3% specificity, showing significant improvements over prior models.

Detection of DR red lesions using augmented 65x65 patches is done [10]. Two CNN models are employed: a pre-trained VGG16 model and a custom CNN with five convolutional

layers, five max-pooling layers, and one fully connected layer. The models are trained on the DIARETDB1 dataset and tested for patch-level classification into red lesions or non-red lesions across multiple datasets, including DDR, IDRiD, MESSIDOR -2, MESSIDOR, Kaggle, and DIARETDB0. After classification, a probability map is generated to categorize images as DR or non-DR. The results show high sensitivity (0.94) and an Area Under the Curve (AUC) of 0.912 for the MESSIDOR dataset, demonstrating the approach's effectiveness in DR lesion detection. In [11], proposes an automated classification approach using a hybrid deep learning model that combines DenseNet121, Xception, and EfficientNetB3. The process begins with preprocessing to enhance retinal image quality, followed by parallel feature extraction using the three pretrained models. The extracted features are concatenated and passed through a classification submodel to determine the severity of DR. Evaluated on the APTOS dataset, the model achieves an accuracy of 86%, highlighting its potential for early and accurate DR diagnosis.

Existing AI models for DR classification face issues like overfitting, limited accuracy, and high computational costs. Hybrid models that combine deep learning with traditional techniques can improve efficiency and performance. Regularization methods such as dropout, weight decay, and augmentation help reduce overfitting and improve generalization. These advancements are vital for reliable deployment in real-world clinical settings. Ultimately, improved models will sup ort early DR detection and better patient outcomes, especially in resource-limited regions.

2.1 GAPS IDENTIFIED THROUGH SURVEY:

- Existing models struggle to accurately detect all four stages of DR, highlighting the need for improved detection capabilities.
- Pretrained models that are completely frozen do not show better performance in DR detection.
- High computational complexity in existing models poses a challenge, necessitating a solution with minimized complexity.

3. OBJECTIVES OF THE RESEARCH

i. Primary Objective:

To develop a model capable of detecting all four stages of Diabetic Retinopathy while reducing computational complexity and maintaining accuracy.

ii. Secondary Objectives:

To fine-tune pretrained models for DR Stages Classification.

To design and evaluate a custom CNN architecture tailored specifically for DR Classification, assessing its performance and efficiency.

To develop a hybrid model combining the strengths of pretrained models and custom CNN architectures, aiming to optimize both detection accuracy and computational efficiency.

4. RESEARCH FRAMEWORK

This research proposes a structured methodology to classify the four stages of DR using deep learning techniques. The primary aim is to develop a robust and efficient DR classification system capable of detecting all four DR stages while addressing challenges such as computational complexity and ensuring model generalization. The methodology is organized into three distinct phases, which align with the research objectives and ensure clinical applicability as shown in the Figure 1.

Phase 1: Fine-Tuning Pretrained Models

In the first phase, transfer learning is applied to fine-tune a high-performance pretrained deep learning architecture for DR classification.

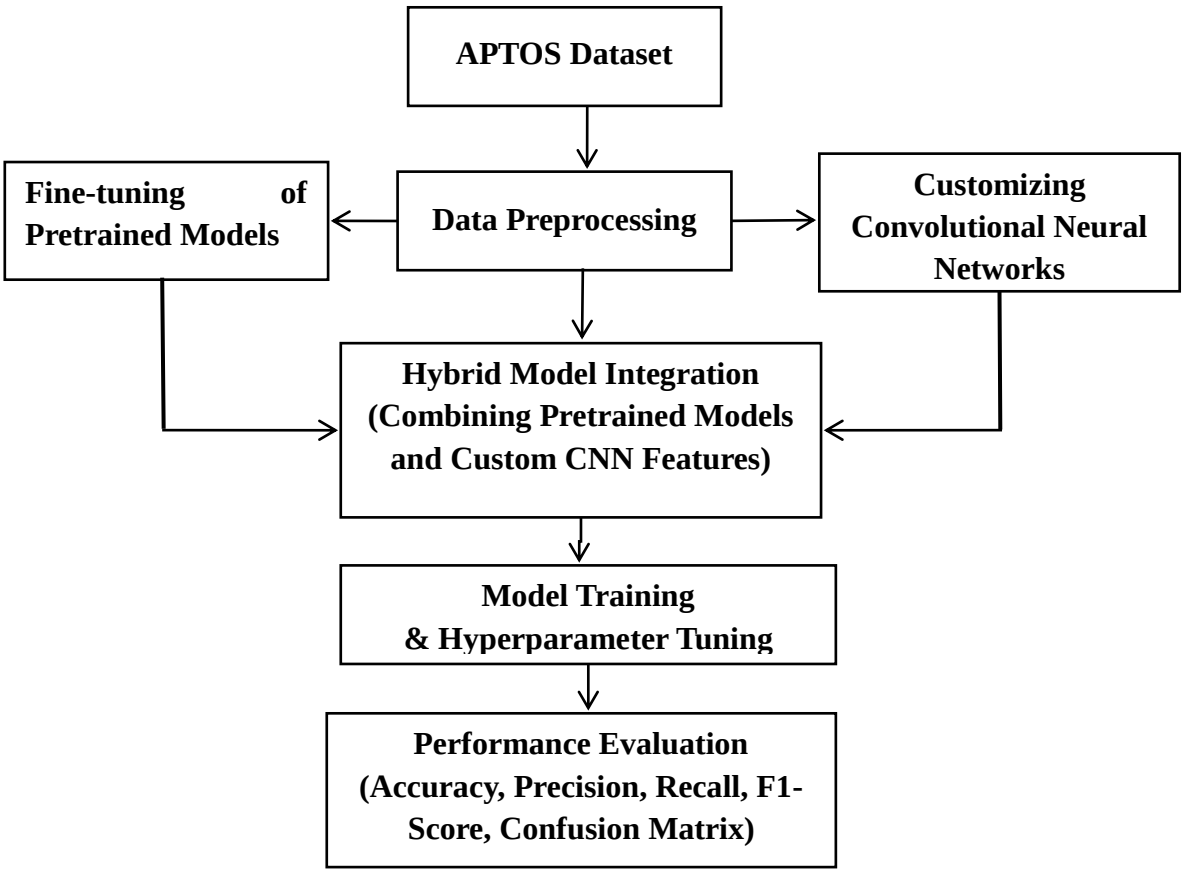
APTOS Dataset
Data Preprocessing
Fine-tuning of Pretrained Models
Customizing Convolutional Neural Networks
Hybrid Model Integration (Combining Pretrained Models and Custom CNN Features)
Model Training & Hyperparameter Tuning
Performance Evaluation (Accuracy, Precision, Recall, F1-Score, Confusion Matrix)

Figure 1 Methodology

Phase 2: Development of a Custom CNN Model

The second phase focuses on designing and developing a custom CNN architecture specifically for DR detection. This model includes convolutional layers, batch normalization, and dropout mechanisms, which help ensure effective feature learning and prevent overfitting. The custom CNN is computationally efficient, making it suitable for clinical deployment, especially in resource-constrained environments where high-end hardware may not be available. It extracts more detailed and specialized features, complementing the pretrained model and improving classification accuracy.

Phase 3: Hybrid Model Integration

The third phase integrates the pretrained model and the custom CNN into a hybrid model. In this architecture, the pretrained model serves as a feature extractor, capturing high-level features from retinal images. These features are then refined by the custom CNN layers, improving the model's ability to classify DR stages accurately.

To optimize the hybrid model, hyperparameter tuning is performed, using methods like learning rate scheduling, batch size adjustment, dropout regularization, and adaptive optimization algorithms (e.g., Adam). This ensures efficient training and convergence while minimizing computational complexity.The performance of all models is evaluated using four metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. The models are trained on the APTOS dataset and validated using clinical data. The hybrid model is finally compared with existing hybrid model that combines DenseNet121, Xception, and EfficientNetB3 to evaluate its performance in terms of classification accuracy, computational efficiency. This comparison ensures that the proposed system is both reliable and scalable for early DR detection and clinical deployment.

4.1.1 PHASE 1: FINE-TUNING PRETRAINED MODELS

The first phase contributes to the field of DR classification using Transfer Learning models. It evaluates several state-of-the-art DL models, including VGG16 [13], ResNet50 [14], InceptionV3 [15], DenseNet121 [16], and EfficientNetV2-L [17], for the task of DR classification. The dataset used in this study is the APTOS 2019 Blindness Detection dataset from Kaggle [18], comprising a total of 3367 retinal images. It is split into 80% training (2697 images), 10% validation (335 images), and 10% testing (335 images) to ensure effective model development and evaluation. By comparing these models based on a metrics such as training

loss, validation loss, training accuracy, validation accuracy. The modal is also evaluated using four metrics Accuracy, precision, recall, and F1 score as shown in the Table 1.

Table 1 Performance metrics for Finetuned Pretrained Models

Architectures	Accuracy (%)	Precision (%)	Recall (%)	F1score (%)
Finetuned VGG16 Model	66	78	61	68
Finetuned Resnet50 Model	73	80	65	71
Finetuned InceptionV3 Model	76	84	73	78
Finetuned Densenet121 Model	87	89	78	83
Finetuned EfficientnetV2L Model	**91**	**90**	**91**	**91**

The Finetuned VGG16 improves with an accuracy of 66%, precision of 78%, recall of 61%, and F1-score of 68%, showing better precision but still room for recall improvement and the Finetuned ResNet50 performs better with an accuracy of 73%, precision of 80%, recall of 65%, and F1-score of 71%, demonstrating stronger learning capability. InceptionV3 offers further improvement with an accuracy of 76%, precision of 84%, recall of 73%, and F1-score of 78%, highlighting its effective learning and generalization. While the Finetuned DenseNet121 excels with an accuracy of 87%, precision of 89%, recall of 78%, and F1-score of 83%, showing superior performance in terms of precision, though recall which is further optimized. Finally the Finetuned EfficientNetV2L leads the comparison with an accuracy of 91%, precision of 90%, recall of 91%, and an F1-score of 91%, demonstrating exceptional performance across all metrics, particularly in recall and F1-score, making it the most reliable model for the task.

4.1.2 PHASE 2: DEVELOPMENT OF A CUSTOM CNN MODEL

The second phase provides a comprehensive comparative analysis of various custom CNN-based models to assess their effectiveness in a classification task. The APTOS 2019 Blindness Detection dataset from Kaggle is used in this study. Initially, the training set contains 2,356 images (70%), which are augmented using techniques such as rotation, flipping, and zooming to address class imbalance, increasing the training data to 5,052 images. The validation and testing sets comprise 672 (20%) and 339 (10%) images, respectively. It is compared based on various performance metrics, including training loss, validation loss, training accuracy, and

validation accuracy. Additionally, the models are evaluated using four key metrics: accuracy, precision, recall, and F1 score, as shown in Table 2.

Among the models tested, Model 5 stands out as the best-performing architecture, achieving the highest accuracy of 0.88. It also maintains a balanced trade-off between precision and recall, which is essential for robust classification. The model's optimized architecture and fine-tuned hyperparameters contribute significantly to its superior performance, making it the most suitable candidate for deployment in practical applications.

Table 2 Performance metrics for five custom CNN models

Custom CNN Models	Accuracy (%)	Precision (%)	Recall (%)	F1score (%)
Custom CNN Model - 1	45	41	45	42
Custom CNN Model - 2	51	46	48	47
Custom CNN Model - 3	60	49	57	53
Custom CNN Model - 4	84	81	80	79
Custom CNN Model - 5	88	86	84	84

Model 1 exhibits the lowest performance with an accuracy of 45% and an F1-score of 42%, indicating difficulties in distinguishing between different classes. Model 2 shows some improvement, but it still faces challenges in generalization. Model 3 demonstrates a notable increase in both accuracy and recall, emphasizing the importance of incremental architectural improvements. Model 4, with an accuracy of 84%, performs well by effectively reducing both false positives and false negatives.

Overall, the analysis shows that improving CNN designs and adjusting hyperparameters are key to boosting model performance. The progressive increase in accuracy from Model 1 to Model 5 underscores the significance of refining feature extraction methods and optimizing network parameters for better classification results. The findings suggest that Model 5 is the best solution for the classification task, with strong generalization and robustness across different classes.

4.1.3 PHASE 3: HYBRID MODEL INTEGRATION

In the third phase, a hybrid deep learning model is developed to enhance the accuracy of DR classification. This model integrates a EfficientNetV2L, a powerful pre-trained architecture, with custom convolutional layers. The goal is to utilize the general feature extraction capabilities of EfficientNetV2L while refining these features using custom CNN layers tailored specifically for retinal image analysis.

For the third phase of the study, the training and validation datasets are sourced from the APTOS 2019 Blindness Detection dataset available on Kaggle. The testing dataset is collected from Kathir Eye Hospital, Tiruchengode, with proper ethical clearance obtained through an Institutional Human Ethics Committee (IHEC) approval letter. To ensure consistency and compatibility across all datasets, comprehensive preprocessing techniques are applied, including brightness enhancement, Contrast Limited Adaptive Histogram Equalization (CLAHE), Gaussian blurring, and sharpening. These steps help standardize the image quality and enhance key retinal features for improved model performance.

EfficientNetV2L is used as the feature extraction backbone. It is pre-trained on ImageNet and fine-tuned to adapt to DR-specific features. By excluding the top layers (include_top=False), only the convolutional layers are used for hierarchical feature extraction. A global average pooling layer converts the extracted features into a compact 1D vector, summarizing high-level visual patterns. This model improves its ability to generalize to fundus images while maintaining computational efficiency and leveraging transfer learning effectively.

The custom CNN layers are designed to extract detailed DR-related features. These consist of four separable convolutional blocks with increasing filter sizes (32, 64, 128, and 256), each followed by batch normalization, ReLU activation, and max-pooling. These layers capture a range of features, from small lesions like microaneurysms to larger signs of retinal damage such as exudates. The use of SeparableConv2D significantly reduces the number of parameters, making the model lightweight and faster to train without sacrificing performance.

Once the EfficientNetV2L and custom CNN layers extract their respective features, they are merged using a Concatenate layer, combining both general and specialized representations. This fusion allows the model to better distinguish between DR stages: normal, mild, moderate, and severe.

The merged features are then passed through fully connected layers, a dense layer with 256 units and ReLU activation, followed by a 30% dropout for regularization, and finally, a SoftMax output layer with 4 units for classification. The detailed flowchart of hybrid model is given in the Figure 2.

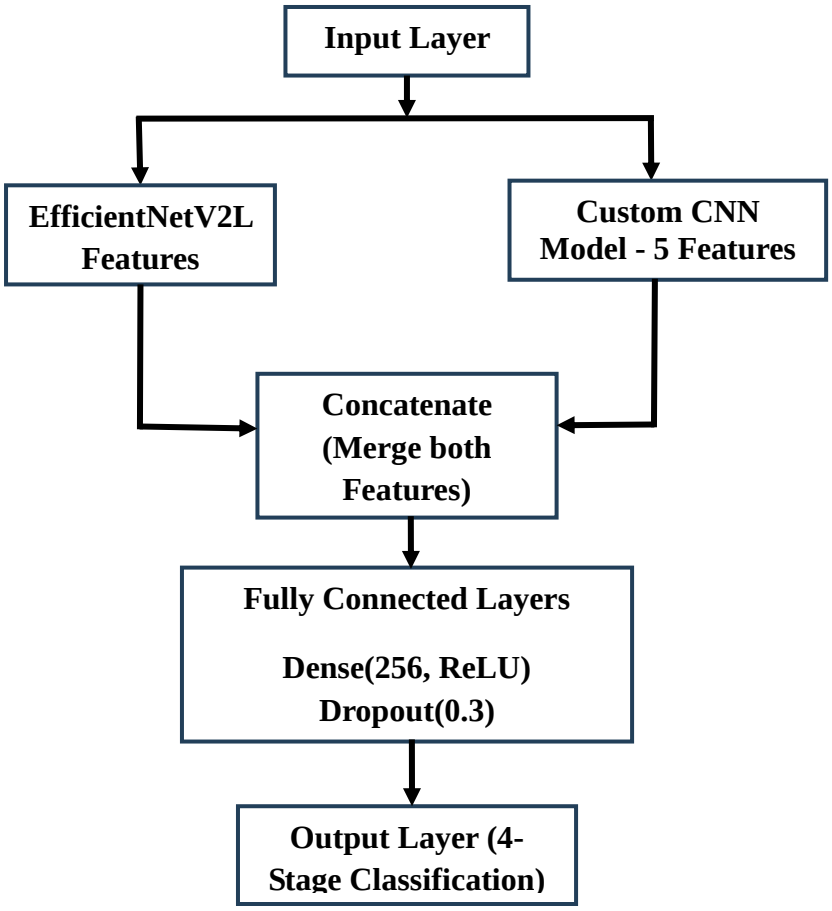

Figure 2 Flow chart of Hybrid Model Architecture

The developed hybrid model is compared against three other models, finetuned EfficientNetV2L, Custom CNN Model 5, and the existing hybrid model that combines DenseNet121, Xception, and EfficientNetB3 to evaluate its effectiveness in DR classification. The comparison is conducted based on key training metrics, including training loss, training accuracy, validation loss, and validation accuracy. In addition to these, the models are evaluated using four core performance metrics: accuracy, precision, recall, and F1-score, which are summarized in Table 3.

Table 3 Modal wise comparison using Performance Metrics

Models	Accuracy (%)	Precision (%)	Recall (%)	F1score (%)	Number of Trainable Parameters	Execution Time (S)
Finetuned EfficientnetV2L Model	91	90	91	91	1,150,724	1.5s
Custom CNN Model - 5	88	86	84	84	1,13,407	1.2s
Hybrid Model – (DenseNet121, Xception, and EfficientNetB3) [19] [2024]	75	73	75	71	2,361,860	3s
Hybrid Model (EfficientV2L and Custom CNN)	**94**	**94**	**93**	**94**	**4,41,087**	**1.6s**

The Testing phase of a model is essential for assessing its generalization capability and determining how well it performs on unseen data. The hybrid model is tested on a set of images representing various stages of the disease: normal, mild, moderate, and severe as shown in Figure 4.

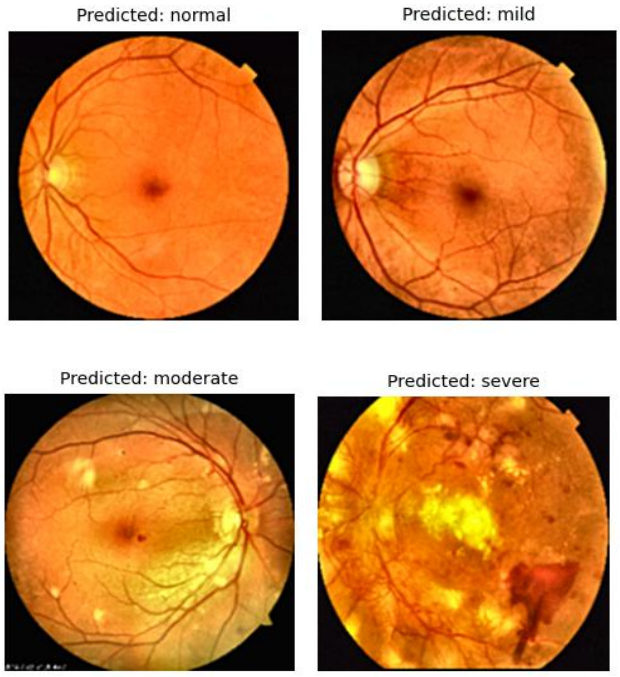

Figure 4 Hybrid model predictions from Custom Set

This hybrid approach ensures robust performance and strong generalization, even on unseen data. By combining the strengths of a pre-trained model with task-specific CNN enhancements, the model achieves high accuracy while maintaining a low parameter count. Its efficiency and adaptability make it suitable for clinical environments, especially where computational resources are limited. The final model demonstrates its potential as a reliable tool for automated DR screening and diagnosis.

5 CONCLUSION AND FUTURE WORK

A hybrid model is developed by integrating fine-tuned pretrained networks with a custom CNN architecture. This design combines the strong feature extraction of pretrained models with the specificity and efficiency of custom CNNs, leading to improved classification performance and computational efficiency in DR stage detection.

Among the fine-tuned models evaluated, EfficientNetV2L shows the highest standalone performance, achieving 91% accuracy, 90% precision, 91% recall, and 91% F1-score. Compared to VGG16, it records notable improvements of 25% in accuracy, 12% in precision, 30% in recall, and 23% in F1-score. For the custom models, Custom CNN Model - 5 performs best with 88% accuracy, 86% precision, 84% recall, and 84% F1-score, surpassing Custom CNN Model - 1 by 43% in accuracy, 45% in precision, 39% in recall, and 42% in F1-score.

When benchmarked against an existing hybrid model (DenseNet121 + Xception + EfficientNetB3, with 2,361,860 parameters), the proposed hybrid achieves significantly higher performance, 94% accuracy versus 75%, with 21% more precision, 18% more recall, and 23% higher F1-score despite using only ~18% of the parameters. In terms of computational efficiency, the proposed hybrid model also excels, requiring only 1.6 seconds for classification, compared to 3.0 seconds taken by the existing hybrid. This shows that the proposed model balances performance, efficiency, and use of parameters effectively.

Future work will focus on enhancing the model's performance and clinical applicability. Advanced regularization techniques and optimization algorithms will be explored to further reduce overfitting and improve generalization across diverse datasets. Real-time deployment using edge devices can enable fast, on-site diagnosis, especially in remote or resource-limited settings. Additionally, integrating Explainable AI (XAI) methods such as Grad-CAM will help interpret model predictions, increasing trust and transparency for clinical use.

6. ORGANIZATION OF RESEARCH

The Thesis is organized into six chapters, each addressing a essential aspect of DR classification using deep learning. **Chapter 1** introduces DR, its clinical importance, and outlines the motivation, objectives, and challenges in automating its detection. **Chapter 2** presents a comprehensive literature review of deep learning methods in medical imaging, particularly DR, identifying limitations in existing models and emphasizing the need for efficient, accurate solutions. **Chapter 3** evaluates fine-tuned pretrained models for DR classification, detailing datasets, training procedures, and performance metrics to identify the most effective architecture. **Chapter 4** describes the development of a custom CNN, highlighting its design, augmentation techniques, and improved performance over standard pretrained models. **Chapter 5** introduces a novel hybrid model combining pretrained and custom layers, compares it with an existing hybrid architecture, and demonstrates its superior performance in classification accuracy and generalization. Finally, **Chapter 6** summarizes key contributions, discusses the impact of the developed models, and proposes future directions, including advanced architectures, real-time deployment, and clinical validation for broader applicability.

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19. Oulhadj, M., et al. (2024). Diabetic retinopathy prediction based on a hybrid deep learning approach. *2024 International Conference on Intelligent Systems and Computer Vision (ISCV)*, Fez, Morocco, 1–5.

LIST OF PUBLICATIONS

International Journals

1. K. Santhiya Lakshmi and B. Sargunam, "Exploration of AI-powered DenseNet121 for effective diabetic retinopathy detection", International Ophthalmology, vol. 44, no. 90, Feb. 2024. (**Web of Science and Scopus - SCIE**)

2. K. Santhiya Lakshmi and B. Sargunam, "The Role of Artificial Intelligence in Enhancing Diabetic Retinopathy Lesion Detection: A Review", Journal of Clinical and Biomedical Sciences, vol. 14, no. 4, pp. 121–128, Dec. 2024. (**UGC Care**)

3. K. Santhiya Lakshmi and B. Sargunam, "A Novel CNN architecture for detecting Diabetic Retinopathy", African Journal of Biomedical Research, vol. 27, no. 4S, pp. 5218–5224, Dec. 2024. (Scopus)

4. K. Santhiya Lakshmi and B. Sargunam, "A Review on recent developments and future research directions on detection of Diabetic Retinopathy by using Digital Image Processing, Machine Learning and Deep Learning", International Journal of Advance & Applied Research, vol. 2, no. 17, pp. 170–180, 2022.

International Conferences

1. Presented a paper titled "Revolutionizing Diabetic Retinopathy Detection: Harnessing the power of CNN" at the Sixth International Conference on Advances in Electrical and Computer Technologies 2024, organized by Sengunthar Engineering College, Tiruchengode, on 26th and 27th September 2024.

2. Presented a paper titled "Detection of Diabetic Retinopathy Stages Using Deep Learning – A Review" at the International Conference on Emerging Trends in Industry 4.0 and Sustainable Concepts, organized by Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, on 24th and 25th February 2023.

3. Presented a paper titled “A Review on Recent Developments and Future Research Direction on Detection of Diabetic Retinopathy by Using Digital Image Processing, Machine Learning and Deep Learning” at the One Day International Multidisciplinary E-Conference on Recent Trends, Challenges and Issues in Science, Social Science and Languages for Sustainable Development, organized by Jawahar Arts, Science & Commerce College, Anadur, in collaboration with Global Foundation, Solapur (Maharashtra), on 4th August 2022.